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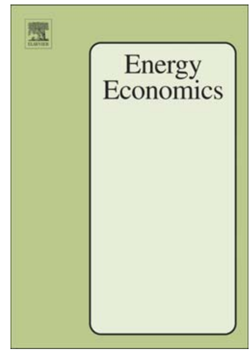

Valuing Smart Meters

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Abstract

This paper assesses to what extent consumers are willing to make use of the features and capabilities offered by smart meters. Via a choice experiment households are offered the choice between a set of smart meters, described by six attributes: impact on the comfort and privacy level, functionality, visibility, cost savings, and investment outlay.

We estimate a main effects conditional logit model and a main effects random parameter logit model, including interactions with socio-demographic characteristics. The results show that households have heterogeneous preferences for some attributes but not for others. The estimates are used to assess marginal willingness to pay values. From a policy perspective, our findings suggest that sufficient effort should be devoted to designing the smart metering devices and to informing households. Without careful preparation, a mandatory or voluntary roll out of smart meters risks to be unsuccessful because device characteristics do not meet consumer needs.

Keywords:
Choice experiment, Smart meter, Conditional Logit model, Random Parameter logit model, Willingness-to-pay.

JEL-classification: C25, D12, Q41

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Valuing Smart Meters

1. Introduction

Lack of demand response is seen as one of the major challenges in the electricity system as it exists today. It is however expected that, driven by technological evolution, demand response will be introduced on a large scale in the next decade or so and that a crucial role in this evolution will played by 'smart meters'.

A smart meter is a device installed at the consumer's premises, that measures real-time electricity consumption in greater detail than conventional meters do and allows two-way communication with the distribution system operator or any other operator that is granted access. This information can then be used for monitoring or billing purposes or to help maintaining the quality of different services provided by utilities (e.g. detection of power outage control, meter reading, simplification of the billing procedure, identifying unauthorized bypass of the meter) (Neenan and Hemphill (2008), Faruqui et al. (2014)). But, perhaps most important, smart meters can also contribute to a more efficient electricity market by conveying information on real-time prices and load to customers, allowing them to respond by increasing or decreasing demand. The magnitude of the response will depend upon the price and/or load information that is communicated, but also on the capabilities of the smart meter and the respondent's willingness to make use of these capabilities. The response itself could be initiated by the consumer, could be automated, or could be left to a third party, for example the distribution company, that remotely controls the usage of electric appliances via the smart metering devices.

Policy makers have recognized the potential benefits of smart meters and have taken several legislative initiatives to increase their market penetration rates. For example, in the US, the Energy Policy Act 2005 and the Energy Independence and Security Act 2007 are at the basis of Federal demand response and smart metering policies. Next to these Federal initiatives, many states have also taken own initiatives. See Pietsch (2012) for a survey. The Federal Energy Regulatory Commission (2013) reports a US (survey based) penetration rate of just over 30% in 2013, coming from 4.7% in 2007. However, penetration rates vary widely from State to State (Federal Energy Regulatory Commission (2012)). In 2012 the three highest penetration rates were found in the District of Colombia (87.1%), California (70.5%) and Idaho (66.1%). Nine states had a penetration rate above 50%, while 26 (15) states had a penetration rate of less than 10% (5%).

In the European Union, the Directives providing the basis for the introduction of smart metering devices are the Energy Services Directive 2006/32/EC, Directive 2009/72/EC, being part of the so-called Third Energy Package, and Directive 2012/27/EU on energy efficiency (Hierzinger et al. (2013)). In summary, these three Directives i) mandate the installation of smart metering devices in all Member States, provided that a roll-out of the devices is assessed positively via a cost-benefit analysis, and ii) expect a positive impact on energy consumption of a timely, clear and frequent communication to customers of their energy use and the related energy cost. Obviously, this presupposes behavioural responses.

In 2013, most Member States had carried out this cost-benefit analysis and a majority was in the process of introducing smart meters in their energy markets, although not all countries have made equal progress (ACER (2013), Hierzinger et al. (2013) and Giordano et al. (2013)). Italy and Sweden have already completed a full roll-out, while another 11 EU Member States have officially decided to go ahead with the roll-out[1]. Three countries have decided not to proceed, based on a negative cost-benefit analysis (Belgium, Czech Republic and Lithuania)[2]. Eleven Member States did not reach a final decision yet[3].

The outcome of these cost-benefit assessments crucially depends on the magnitude of demand response that is triggered. Faruqui and Sergici (2010), Faruqui and Palmer (2012), Newsham and Bowker (2010) and Stromback et al. (2011) survey the results of recent pilots and field experiments of smart metering and dynamic pricing, both in the US and worldwide. They all conclude that households do indeed respond to higher prices by lowering demand, but also that the magnitude of the response, measured as the percentage reduction of peak demand, depends on a number of elements of which the type of pricing scheme is only one[4].

Another element, also mentioned as important, is technology. The same survey studies report that the magnitude of demand response significantly increases when enabling technologies such as, for example, two-way communication, smart thermostats or in-home displays are used. This is confirmed by Joskow (2012), who concludes that technologies and information that make it easier for consumers to respond to price signals lead to larger responses to any given price change, suggesting that the functionalities of the smart metering device are important. Furthermore, Giordano et al. (2013) also conclude from the pilots they survey that long term sustainable change in electricity usage can only be achieved when enabling technologies and automated systems are used.

However, Giordano et al. (2013) and Stromback et al. (2011) stress that, next to enabling technologies, a successful roll-out of smart meters will also crucially depend on consumer engagement. They note that consumer resistance can be a significant barrier and thus remains a key issue. Violations of privacy and fear of losing control over electricity usage are two examples that could feed this consumer resistance (Krishnamurti et al. (2012) and Joskow (2012)).

The importance of consumer engagement is illustrated by Faruqui et al. (2010). They estimate that the present value of the net benefits of rolling-out smart meters in the EU could be in the order of magnitude of €50 billion, on the condition that dynamic pricing schemes are successfully introduced and used on a large scale. When dynamic pricing schemes are not offered by suppliers or not used by the customers, then much of the potential benefits of smart metering will however not be realized. This could make the difference between negative and positive net benefits for the EU smart metering project as a whole.

1 These countries are Austria, Denmark, Estonia, Finland, France, Ireland, Luxemburg, Malta, Spain, The Netherlands and the UK.

2 Based on data collected from the National Regulatory Authorities, the Council of European Energy Regulators (2013) reports on the results of the assessment exercises in the European Union. 18 countries carried out a CBA, 13 of which resulted in a positive outcome and 3 in a negative outcome. For two countries (Denmark and Portugal) the outcome is unknown.

3 These countries are Bulgaria, Cyprus, Germany, Greece, Hungary, Latvia, Poland, Portugal, Romania, Slovakia and Slovenia.

4 Note that research on (the magnitude of) demand response is ongoing, as is illustrated by the EU FP7 ADVANCED (Active Demand Value ANd Consumers Experience Discovery) research project (http://www.advancedfp7.eu/). This project aims at drawing lessons from the analysis of available data of four real live demonstration projects, the VaasaETT database and many other active demand databases with secondary data. Other research projects in the field of smart grids and smart metering are the European FP7 ADDRESS project (http://www.addressfp7.org/) and the Meter-ON project (http://www.meter-on.eu/).

In this paper we concentrate on the link between enabling technologies and consumer engagement. Our question is to what extent consumers are willing to make use of the features and capabilities offered by smart meters. Thus, we do not focus on the role of dynamic pricing schemes, as it is done in many pilot studies and field experiments, but rather on the impact of the features and capabilities of the devices as such. Essentially, we want to find out to what extent households are willing to use the capabilities offered by smart metering devices.

A choice experiment was set up in which smart metering devices, differing in terms of 6 characteristics, are being offered to consumers. Based on their stated choices, we then estimate the value of each of these attributes and of the devices as a whole. The choice experiment was carried out in Flanders in the first half of 2011 and was part of a master thesis project done in the context of an exploratory market study for a small technologic firm. We think that, despite the relatively limited number of respondents and the deficiencies of the sampling approach, the conclusions are valuable and useful for both public and private policy making as the policy debate regarding a mandatory or voluntary roll-out of smart metering devices is ongoing in many countries. The results allow to identify the positively and negatively valued attributes of the metering devices, and may thereby increase the likelihood of a successful roll-out.

Whereas in the past revealed preference approaches were mostly used to assess preferences, we now observe that, for many applications, more and more use is being made of stated preference techniques. A stated preference method, more specifically a choice experiment, will also be used in this paper. To our knowledge, a similar exercise has not been made before in the context of smart metering devices.

Choice experiments have however been used in other energy related areas. For example, Bergmann et al. (2006) use a choice experiments to investigate the WTP for green electricity, where green energy is described in terms of its environmental attributes, such as, landscape impact, wildlife impact and air pollution. Longo et al. (2008) have set up a choice experiment in which four potential effects of a renewables policy are being considered: GHG emission reductions, short term security of supply (blackouts), employment effects and the price impact. Scarpa and Willis (2010) investigate the households' WTP for renewable micro electricity generation technologies in the UK, while Borchers et al. (2007), use choice experiments to focus on the input side of green electricity rather than on the output side. Revelt and Train (1998) use a choice experiment to assess the relative value for households of refrigerators with different efficiency levels. Banfi et al. (2008) focus on the WTP of households, either owners or tenants, for air renewal systems and improved window and facade insulation, while Shen and Saijo (2009) use the choice experiment approach to assess the impact of energy efficiency labels on the consumer's WTP for air conditioners and refrigerators in Shanghai. In the context of short term security of supply or power outages, choice experiment applications can be found in Beenstock et al. (1998), Carlsson and Martinsson (2008) and Pepermans (2010).

The following section briefly introduces the choice experiment methodology, some relevant literature and the techniques used in this paper to estimate the preference structure. The sections 3 and 4 then describe the Belgian and Flemish electricity market and the data, respectively. Section 5 discusses the estimation results. Finally, section 6 concludes.

2. Methodology

The basic idea of a choice experiment is quite simple: respondents are asked to evaluate sets of hypothetical items (goods, services, options, projects…). Each item is described by a number of typical characteristics or attributes and within each set, the respondent then has to indicate the item he or she prefers. These stated choices reveal information about preferences and can be used to assess the relative value of the different attributes describing the items[5].

2.1. Theoretical background

Choice experiment data are typically analyzed with conditional logit (CL) models. As Train (2003) and Moore (2008) point out, one drawback of the standard conditional logit model is that homogenous preferences are assumed. We will therefore also present the results of a Random Parameters (RP) or Mixed Logit Model (Train (2003)) as an alternative approach that allows for preference heterogeneity. In the random parameter model, unobserved preferences are assumed to follow a predefined structure. Individual-specific covariates can be added as interaction variables to further explain this preference heterogeneity. The parameters of this pre-imposed preference structure are estimated together with the parameters of the other covariates. See Morey and Rossmann (2003) and Moore (2008) for illustrations of this approach.

Alternatively, heterogeneous preferences could also be introduced via a latent class model along the lines of Morey et al. (2006) or Boxall and Adamowicz (2002). Morey et al. (2006) considers group or class membership as exogenous, whereasBoxall and Adamowicz (2002) assume group membership to be endogenous. Moore (2008) compares the three modeling approaches and concludes that assuming heterogeneous preferences adds to the explanatory power of the models. Furthermore, he finds that, despite differences in the underlying assumptions and in the parameter estimates, the WTP-estimates derived from the three models show little difference. Therefore, from a policy perspective the main message is that it does not matter how preference heterogeneity is included in empirical models, as long as it is included. In this paper, we will thus use the mixed logit approach to allow for heterogeneity in preferences.

2.1.1. The Random Utility Model

The Random Utility Model (RUM) is used to analyse household preferences. The RUM is based on random utility theory which starts from the assumption that decision units maximize utility. Let decision unit n face T consecutive choice problems each of which implies a choice to be made between J alternatives. From each alternative j, a utility level U_{njt} can be obtained, which is known to the decision unit but is only partially observed by the researcher, i.e.

$$U_{njt} = V_{njt} + \varepsilon_{njt} \tag{1}$$

with V_{njt} observed utility and ε_{njt} unobserved utility, represented as a random term. For each choice problem C, a decision unit will select the alternative that provides maximal utility. The presence of the random component in equation (1) implies that only

[5] We refer to Bateman et al. (2002) and Amaya-Amaya et al. (2008) for a more elaborate discussion of the choice experiment technique.

probabilistic statements can be made about the decision unit's choices. Thus, the probability of choosing alternative j from choice set C can be written as

$$\begin{aligned} P_t\left(j\middle|C\right) = P_{njt} &= P_t\left(U_{njt} > U_{nit}, \forall i \neq j \in C\right) \\ &= P_t\left(V_{njt} - V_{nit} > \varepsilon_{nit} - \varepsilon_{njt}, \forall i \neq j \in C\right). \end{aligned} \tag{2}$$

Assuming that ε_{njt} is i.i.d. type I extreme value and that observed utility is linear in the parameters (i.e. $V_{njt} = \beta x_{njt}$), it can be shown that

$$P_{njt} = \frac{e^{\beta x_{njt}}}{\sum_{i \in C} e^{\beta x_{nit}}} \tag{3}$$

with x_{njt} a vector of alternative-specific attributes and β the vector of parameters to be estimated. Equation (3) defines the conditional logit model which is the basic model to analyse conjoint choice data.

The conditional logit model assumes homogeneous preferences, which is a rather extreme assumption that can be relaxed either by interacting socio-demographic characteristics with product attributes or by allowing tastes to vary over the population with density $f(\beta)$ (Train (2003)). In the latter approach, we can then rewrite observed utility as $V_{njt} = \beta_n x_{njt}$, where the heterogeneity of preferences is now made explicit by indexing β. Note that β_n is assumed constant over time, i.e. preferences of decision unit n are stable over consecutive choice situations, which for the current application is a realistic assumption. In this paper, we assume all preferences to follow a normal density, except for the preferences for cost savings which follow a lognormal distribution.

Assuming that ε_{njt} is i.i.d. extreme value over decision units, alternatives and time, we can write the conditional probability that a decision maker will make a given sequence of choices $\mathbf{j} = \{j_1, j_2, ..., j_T\}$ as

$$\mathbf{L}_{n\mathbf{j}}(\beta_n) = \prod_{t=1}^{T} \frac{e^{\beta_n x_{njt}}}{\sum_{i \in C} e^{\beta_n x_{nit}}}.$$

As the researcher does not know β_n, he or she has to consider all possible values of β to arrive at the unconditional choice probability of decision unit n choosing the sequence of alternatives $\mathbf{j}$:

$$P_{n\mathbf{j}} = \int \left\{ \prod_{t=1}^{T} \frac{e^{\beta_n x_{njt}}}{\sum_{i \in C} e^{\beta_n x_{nit}}} \right\} f\left(\beta \middle| \mu_\beta, \sigma_\beta\right) d\beta. \tag{4}$$

Equation (4) cannot be solved analytically, but simulation techniques can be used to solve for the preference parameters that maximize the simulated log-likelihood function[6] (Train (2003)).

2.1.2. Model specification

In its most general form, observed utility derived from alternative i is written as (the subscript n is omitted to simplify notation):

$$U_{it} = \sum_{j \in C} \beta_j^{ASC} ASC_j + \sum_k \left(\beta^k + \eta^k + \sum_m \alpha^m Z^m \right) X_{it}^k + \beta^I I_{it} + \varepsilon_{it} \tag{5}$$

where ASC_j is a dummy variable equal to 1 if $j = i$ and zero otherwise, X^k is attribute k and I is a continuous variable expressing the monetary attribute (investment outlay in euros). The variables Z^m are socio-demographic characteristics. Finally, η^k reflects individual specific preference deviations, i.e. remaining unexplained heterogeneity in preferences. The variables Z^m and η^k will be introduced in the mixed logit model but not in the conditional logit model.

Although the choice experiment approach does not provide direct WTP estimates, these values can be estimated indirectly via the estimated parameters of equation (5). In the next section we will discuss how this can be done.

2.2. Estimating the Willingness-to-Pay

Under the assumption of a standard conditional logit model with observed utility linear in income (see eq. (5)) , the consumer surplus associated with a set of alternatives takes a closed form that is easy to calculate (see also Train (2003)). The consumer surplus derived from the chosen alternative i is simply the utility derived from that alternative, expressed in monetary terms. Knowing that a decision maker chooses the alternative that maximizes his or her utility, the consumer surplus is

$$CS_n = \frac{1}{\beta^I} \max_{j \in C} \left(U_{nj} \right) \tag{6}$$

with β^I representing the preference parameter related to the monetary attribute. Dividing by β^I converts utility into monetary terms. However, the researcher does not observe the utility U_{nj} linked to the utility maximizing alternative. He only observes V_{nj} and he knows the distribution of the error term. Therefore, only expected consumer surplus can be calculated, i.e.

$$E\left(CS_n\right) = \frac{1}{\beta^I} \mathrm{E}\left(\max_{j \in C} \left(V_{nj} + \varepsilon_{nj} \right) \right) \tag{7}$$

McFadden (1973) and McFadden (1995) show that, if ε_{nj} is i.i.d. extreme value and utility is linear in income (i.e. β^I, the marginal utility of income, is constant), then this expression reduces to[7]

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[6] Actual estimations were done with STATA's *mixlogit* procedure.

$$E\left(CS_n\right)=\frac{1}{\beta^I}\ln\left(\sum_{j\in C}e^{V_{nj}}\right)+K \tag{8}$$

with K a number known as Euler's constant. An alternative interpretation of equation (8) is that $E\left(CS_n\right)$ is the average consumer surplus in the subpopulation of people who have the same representative utilities as consumer n. The total consumer surplus can then be calculated as the weighted sum of $E\left(CS_n\right)$ over a sample of decision makers, with the weights reflecting the number of people in the population who face the same representative utilities as the sampled person (Yu (2003), p. 60).

The change in consumer surplus that results from *a change in the alternatives* and/or the choice set is then equal to

$$\Delta E\left(CS_n\right)=\frac{1}{\beta^I}\left\{\ln\left(\sum_{j\in C_{After}}e^{V_{nj}^{After}}\right)-\ln\left(\sum_{j\in C_{Before}}e^{V_{nj}^{Before}}\right)\right\} \tag{9}$$

When the purpose is to *compare two alternatives* or profiles, for example the base case (the *status quo)* and an altered case, and if both deterministic utility terms between accolades are linear in the attributes, then equation (9) reduces to

$$\Delta E\left(CS_n\right)=\frac{1}{\beta^I}\left\{V_n^{After}-V_n^{Before}\right\} \tag{10}$$

If the purpose is to evaluate the *change in one attribute* and if deterministic utility is linear in the attributes, then equation (10) further reduces to the ratio of the marginal utility of the attribute and the marginal utility of income, also known as the *marginal willingness to pay* (Champ, Boyle *et al.* (2003), p. 195-196).

For models in which only main effects are estimated (as will be the case in this paper), the marginal willingness to pay by household n for a change in a single attribute k is defined as

$$WTP_n^k=-\left(\frac{\beta^k+\eta^k+\sum_m\alpha^m Z_n^m}{\beta^I}\right) \tag{11}$$

3. Background information on the Belgian and Flemish electricity market

Flanders is one of the three regions in Belgium, next to Wallonia and Brussels Capital Region. Energy competences in Belgium have been divided between the Federal state and its three regions. Competences related to non-renewable electricity generation capacity and transmission are allocated to the Federal level, while competences related to distribution and retail activities, to energy efficiency, and renewable policy are allocated to the regions. The Belgian electricity market counts about 5.3 million residential customers, of which 2.7 million customers are Flemish residents (VREG (2013b)).

[7] A more complex formulation of the change in consumer surplus is needed when the marginal utility of income is not constant. However, when marginal utility of income is constant over a range of income levels that correspond to the policy, then equation (8) can also be used (Train (2003), p. 61).

In 2013, 12 distribution companies took care of electricity distribution in Flanders. Distribution companies are at least partially owned by the municipalities. In some distribution areas, the incumbent generator Electrabel is also involved. These latter distribution companies have joined their operational tasks in one coordinating company, Eandis, which is jointly owned by the municipalities (79%) and Electrabel (21%). The distribution companies fully owned by municipalities have joined their operational tasks in another coordinating company, Infrax.

Retail competition is allowed. In December 2012, 33 firms had a license to supply electricity to end-users, 14 of which also focused on the residential market. Not all retailers are actively supplying in all distribution areas, but all areas count at least 10 active retailers. In 2012, three suppliers had a market share of more than 10% (VREG (2013b)). Electrabel Customer Solutions is the largest player with a market share of 39.7%, coming from 48.1% in 2010. EDF Luminus with 20.5% and Electrabel NV with 16.2% are also in the top three. The latter firm only supplies to large companies and the government. Five firms have market shares of more than 1%; all other firms have lower market shares.

Note that two of the three largest suppliers, Electrabel Customer Solutions and Electrabel NV, are controlled by GDF Suez. Nevertheless, concentration measures in the sector are improving. For example, in 2012 the HHI-index for the Flemish electricity retail sector was 3094, coming from 4595 in 2010.

Two pricing schemes are used in the Flemish residential electricity market: a flat tariff and a time-of-use tariff. Survey results indicate that the TOU market share is steadily increasing[8], reaching 49.5% in 2011 (VREG (2011)). Electricity consumption is being registered once per year by the metering company, either via a visit from a company representative or via self-reporting by the household. Electricity bills are sent out every three months, based on expected expenses for the coming year after the last meter reading. In the last quarter of the billing period, a final bill is presented, based on the actual or reported meter reading. Remarkably, the survey results also mention that more than 45% of households have no idea of their level of electricity consumption (measured in kWh). Moreover, about 20% of households do not check electricity bills.

3.1. Smart metering initiatives in the Flemish electricity market

The introduction of smart meters in Belgium has been stalled because of contradictory outcomes of economic cost-benefit analyses in the regions. A first cost-benefit analysis for the Flemish market showed a negative business case (Schrijner et al. (2008)). The analysis was updated in 2011 (Schrijner et al. (2011)), resulting in a slightly positive business case for a complete rollout. In cases, the same framework and model was used. The switch from a negative to a positive business case was driven by parameter updates based on new information. However, to date, Flanders did not take a formal decision regarding the introduction of smart meters yet, but the topic is expected to stay high on the agenda of most stakeholders.

8 About 5% of residential customers also have a separate meter and a corresponding flat tariff for electricity consumption during the night. This tariff applies to customers using particular types of electrical heating and is usually combined with a TOU tariff for non-heating related electricity consumption.

Eandis and Infrax initiated and finalised some small scale pilot projects, with a specific focus on technical testing, both of the meters and the communication technology[9]. As of October 2012, both companies started with installing about 50.000 smart meters at representative locations in Flanders (urban and rural areas, apartments…). The outcomes of this latter project should allow updating previous findings that were based on the small scale pilot studies. In March 2014, another update of the CBA study was made, taking into account these newly collected data. The conclusion of this study was that the business case for a mandatory and full rollout still is negative (VREG (2014)).

The Flemish energy regulator VREG annually publishes a so-called Market Monitor based on a survey conducted on 1000 Flemish residential customers. The questionnaire also includes a few questions on the consumer's interest in, perception of and attitude about smart meters. In the survey, a smart meter is defined as a device that registers energy use in detail and that provides faster, better and more frequent information about usage. The question is asked whether the respondent would be interested in receiving a smart metering device from their distribution company. Summarizing, VREG (2012) and VREG (2013a) report that females, younger cohorts, respondents with more educational background, and employed respondents show more interest in smart meters than their complementary counterparts.

Finally, VREG (2012) also reports that about 18% of the respondents consider a smart meter as described above as an invasion of privacy. Also, 71% of respondents strongly opposes to the possibility of a temporary interruption of power supply. Of the remaining fraction, 26% would accept a temporary and partial interruption of supply, and 2% would accept a temporary and full power cut.

4. The data

The data for this study were collected in the Flemish residential electricity market as part of an exploratory market study for a small technological firm that planned to introduce its own smart metering technology. Based on a literature survey and a pilot study, we identified six attributes and corresponding levels to describe a smart meter (Table 1).

Obviously, potential cost savings are an important characteristic of any smart metering device. Six levels of cost savings were considered. At the explicit request of the firm, the highest level offered was 60% of cost savings per year, which is very high. Such high levels of cost saving might play a dominant role in people's choice behaviour and could bias the estimation results. We will therefore check for such dominant choice behaviour in the empirical section and take corrective actions, if necessary.

Comfort and privacy impact, and the functionality of the devices are mentioned in many studies and discussions as relevant aspects to take into account. Each of these attributes could take three qualitatively described levels.

Using such extreme levels of potential cost savings creates an important point of concern. While moderate levels of cost savings are feasible with no or limited impact on comfort, high levels of cost saving will very likely result in a reduced comfort level, unless households were extremely inefficient in their electricity consumption at the start. The 'cost saving' and 'comfort impact' attributes as defined in this study are thus

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[9] See http://www.linear-smartgrid.be for a brief description of one of the small scale pilot projects in Hombeek, Leest and Bret-Gelieren.

correlated in practice. A smart metering profile resulting in a 60% annual cost reduction without impact on comfort is not very realistic and respondents might face difficulties when facing such apparently illogical combinations. However, our design does allow for such combinations.

With hindsight, this could and should have been taken into account in the experimental design by prohibiting implausible attribute-level combinations and by allowing for interactions between the cost savings and the comfort attribute, and between all other two-way attribute combinations for that matter. The consequences of this for the estimated preference weights and the WTP values will be further discussed in section 5.

The visibility attribute was added at the explicit request of the firm as it was still considering different design options. Finally, the investment cost was added as the monetary attribute, allowing to calculate WTP values. The selected range of investment cost levels is in line with Giordano et al. (2013) who report that, depending on scale, communication technology, implemented functionalities and specific local conditions, the cost per device in current European pilot studies varies between €100 and €400 per device.

Respondents were told they had the choice to either buy a smart meter with the specified characteristics or to keep the currently installed standard meter[10]. Throughout the survey, it was implicitly assumed that the metering device had an infinite lifetime.

The choice experiment had a full factorial design of $6 \times 3^5 = 1458$ profiles. Following the principles outlined by Street et al. (2005), we selected a subset of 36 profiles and created 18 choice sets such that – with some loss of information – the most important and relevant effects could be estimated. The design used in this paper allowed estimating all main effects while giving maximal consideration to balancing, orthogonality and minimal overlap of levels within choice sets[11].

INSERT TABLE 1 ABOUT HERE

An opt-out option was included in every choice set, allowing respondents not to purchase or indicate any of the proposed devices. Asking respondents to evaluate 18 choice sets was considered not realistic, and we therefore created two blocks of 9 choice sets. Respondents were asked to evaluate one of these blocks, based on whether they were born in an odd or even month. A small pre-test showed that respondents considered evaluating 9 choice sets a feasible and not too burdensome task.

The analysis in this paper is based on a survey covering 287 households. For some households the responses could not be used due to missing or inaccurate data, mainly regarding the size of the electricity bill. Cleaning up the responses resulted in a dataset containing 228 households. As explained before, two blocks of 9 choice sets were constructed, the first block was evaluated by 116 respondents, the second block by 112

[10] See appendix A for an example of the choice experiment question as it was used in the questionnaire.

[11] According to Louviere (1988), main effects explain between 70% and 90% of respondent behaviour. The efficiency of the fractional factorial designs has not been explicitly evaluated.

respondents. Data collection took place in the first semester of 2011 via a web-based survey[12].

The purpose was to carry out an exploratory study and to gather information about preferences regarding smart metering devices, both from individuals with a revealed interest in electricity products and services and from individuals without apparent interest in these products and services. As it was conjectured that younger, well-educated households and/or households living in relatively new houses would show more interest in smart meters, we decided to aim at an oversampling of younger and middle aged cohorts. A strict budgetary constraint imposed by the client firm made us decide to use the snowball sampling technique to collect the data. The survey was launched in two ways. First, a link to the survey was emailed to an extensive list of contacts collected by the stakeholders involved (relatives, friends, acquaintances). Most of these contacts had no apparent interest in electricity products or services. Second, a link to the survey was posted on three websites that are primarily visited by people interested in energy issues, products and services.

Clearly, snowball sampling has a number of deficiencies of which sample selection bias is probably the most important one. The selection of the sample is not random and one can therefore not make general claims based on this particular sample. However, a major advantage in the context of the current study was the low cost involved in using a snowball sample. Moreover, as the snowballs began with the researchers and as respondents were either acquainted with energy or with one of the researchers, the response rate and the willingness to participate in further redistributing the survey link was quite high.

The survey had three parts. The first part collected information on the respondent's knowledge and attitudes about smart metering. These questions helped to prepare the respondent for the choice experiment and the answers were used to construct a variable that measures a respondent's level of knowledge regarding smart metering. This variable was used as a covariate in the mixed logit model. The second part of the survey contained the choice experiment. As discussed, the choice experiment was kept fairly simple and straightforward and we therefore did not expect too many difficulties for respondents to answer these questions[13]. Finally, in the third part of the survey we collected information on some relevant socio-demographic characteristics such as household size, education and household income level.

Table 2 summarizes some descriptive statistics for the cleaned database and the corresponding values for the Flemish population. Clearly, respondents younger than 35 are overrepresented in the sample. Also, the average level of education and, consequently, the net monthly income level are higher in the sample than in the Flemish population. This is what we expected and in order to (partially) control for their effects, we include some socio-demographic covariates as control variables in the estimations.

INSERT TABLE 2 ABOUT HERE

[12] For a comparison and discussion of face-to-face and web surveys, we refer to Nielsen (2010). This author concludes that, for his study, the mean and median WTP values are statistically indistinguishable for both survey modes, despite the fact that response rates and other validation criteria can differ significantly.

[13] Appendix B presents a description of the 18 choice sets and the frequencies with which every profile was chosen in every choice set.

The overrepresentation of younger and highly educated respondents in the higher income classes will likely affect the estimates presented in section 5. Based on what is reported by VREG (2013a) in terms of interest shown in smart metering applications, we would expect preferences and WTP values for smart meters to be higher in these socio-demographic classes.

As expected – due to the overrepresentation of high income households – the average electricity bill in our sample (€1087) is higher than the average bill according to the Household Budget Survey 2012 (€836)[14]. We did not collect data on actual electricity consumption (expressed in kWh). However, based on an annual survey, the Flemish regulator reports an average household electricity consumption of 3983 kWh in 2011 (VREG (2012)). This average consumption covers all Flemish households, irrespective of their tariff scheme. Jespers et al. (2012) report Flemish survey data on average residential electricity consumption per type of housing. Using weights based on the type of housing, a weighted average annual electricity consumption of 3942 kWh was found which is close to the average consumption reported by VREG (2012). Given the higher electricity bill in our sample, we can conjecture that the average level of electricity consumption in our sample is above the Flemish average[15].

The Federal Energy Regulator CREG regularly reports on the evolution of the cost of energy (electricity and gas) for standard consumers. One type of standard consumer is a 4-person[16] household consuming 3500 kWh per year (1600kWh daytime/1900kWh during the night and weekend) subject to a TOU pricing scheme. Early 2011, this standard customer would, given market conditions at that time and depending on the distribution area and the supplier, be paying an overall average price per kWh between €0.160 and €0.210.

4.1. Familiarity with the technology

A respondents' familiarity with the smart metering technology was assessed based on the self-reported level of knowledge of smart grids and smart homes. Two questions were asked at the start of the survey: 'how would you describe your knowledge of smart grids?' and 'how would you describe your knowledge of smart homes?'. Both questions were preceded by a brief description of the main features of a smart grid or smart home. Answers on both questions were provided on a 4 point scale (extensive, good, poor, none) and were then combined into one variable. Respondents with extensive or good knowledge of either smart grids or smart homes were classified as having 'good prior knowledge', respondents with poor or no knowledge of both smart grids and smart homes were classified as having 'no prior knowledge'. All others were classified as respondents with 'some prior knowledge'. In this way, 14% of respondents are classified as having good prior knowledge, 79.4% is classified as having 'no prior knowledge' and 6.6% is classified as having 'some prior knowledge'. The level of

[14] See http://statbel.fgov.be/nl/statistieken/gegevensinzameling/enquetes/huishoudbudget/. Only available in Dutch or French.

[15] We could also estimate average electricity consumption in our sample by dividing the bill by the average price per kWh. However, such a calculation would require information on the share of households in the sample paying a flat rate or a TOU rate, respectively. We do not have this information. Moreover, this approach would be further complicated by the fact that flat and TOU rates tend to differ substantially between distribution areas.

[16] In Flanders, households receive a rebate (known as free electricity) that depends on household size. This rebate equals $(\text{Number of household members}+1)\times 100kWh\times \text{price}_{kWh}$ and was taken into account in the calculation. In practice, the cost of this rebate is socialized via the distribution tariff.

knowledge seems to depend on age but not on income. About 68% of respondents younger than 36 were classified as having no prior knowledge, increasing to 78% and 92% in the medium age class and 50 plus age class, respectively.

INSERT TABLE 3 ABOUT HERE

Only 8 respondents made use of some kind of smart metering application in their house. One question measured the extent to which respondents are interested in the different capabilities of a smart meter (measuring standby consumption, consumption per device, timing of consumption, and automated response to real-time prices). The results are summarized in Table 3. Overall, a majority of respondents showed positive and fairly stable interest in the capabilities of smart meters: 18% to 24% is not or moderately interested, 45% to 55% is highly or extremely interested.

5. Estimation results

It has been described in the literature (for example Rose and Bliemer (2009)) that optimal orthogonal designs may stimulate apparent lexicographic choice *behaviour*, particularly when dominant attribute levels are used. As explained before, this might be the case with the cost savings attribute in our choice experiment. Such behaviour would manifest trough a systematic choice of the alternative that ranks best on that attribute, irrespective of the other attributes shown in the choice set. Lexicographic choice behaviour could also manifest through a repeated selection of the status quo option (non-participation) or through a number of other routes, such as simplifying strategies or heuristics, ethical reasoning or actual lexicographic preferences (Campbell et al. (2008), Sælensminde (2006)). Lancsar and Louviere (2006) argue that, as lexicographic choices do not necessarily represent lexicographic preferences, deleting observations based on what appears to be lexicographic choice behaviour might lead to biased results. They therefore advice to be cautious when considering deleting responses from discrete choice experiments based on the alleged presence of irrational choice behaviour. If researchers have doubt regarding the rationality of choices stated by some respondents, then they advise to at least present the models estimated with the data in and out of the model. Data should only be removed from the dataset if there is strong theoretical and empirical evidence to do so.

Following their advice, we present estimates for the CL model with and without observations of respondents showing non-compensatory behaviour and then test whether the results are different[17]. We define apparent lexicographic responses as responses where the respondent has consistently chosen the alternative with the ‘best level’ for a given attribute (Ryan and Bate (2001), Rulleau and Dachary-Bernard (2012)). For the monetary attributes, apparent lexicographic preferences were identified when higher (lower) values for the cost savings (investment cost) attribute were consistently preferred above lower (higher) values in all choice sets. For the qualitative attributes, responses were identified as apparently lexicographic when the respondent consistently preferred the alternative with the same level in all choice sets (if that level

[17] An alternative to dropping respondents from the sample is to treat preference discontinuity parametrically by adjusting the statistical model. See Campbell et al. (2008), Campbell et al. (2011), Scarpa et al. (2013) and Hole (2011) for examples of this approach.

was present in the choice set). Non-participation is identified as consistently preferring the status quo alternative above any other alternative offered in all evaluated choice sets (Hess et al. (2010)).

Unsurprisingly, we found indications of apparent lexicographic choices in the cost savings attribute as 29 out of the 228 respondents systematically chose the alternative with the highest level of cost savings. We did not find indications of lexicographic choice behaviour for the other attributes. Non-trading behaviour was found in the stated choices of 12 respondents.

Finally, note that, despite the corrections for non-compensatory behaviour, it remains the case that the values for the cost savings attribute levels are high, also for those respondents that do not show non-compensatory behaviour according to the definitions used above. This could still have a positive impact on the size of the estimated preference weight for the cost savings attribute and thus also on the calculated WTP value. This is yet a second reason why the WTP values calculated for the cost savings attribute are probably best interpreted as upper bounds to the real WTP[18].

5.1. The conditional logit model

Table 4 shows results for the main effects CL model without socio-demographic interactions, i.e. the following special case of equation (5) was estimated:

$$U_{it} = \beta^{ASC} ASC_{SQ} + \beta^{CostSavings} X_{it}^{CostSavings} + \sum_{k=1}^{K} \sum_{l=1}^{L_k - 1} \beta_l^{\,k} E_{lit}^{k} + \beta^{I} I_{it} + \varepsilon_{it}\,, \tag{12}$$

where the $K = 4$ qualitative attribute variables are coded into $L_k - 1$ effects (E) each[19]. Effects variables corresponding to the current situation, i.e. the status quo (SQ) alternative, are all set equal to zero. In the non-status quo alternatives, reference levels for the categorical attributes (see Table 1) are indicated by -1. The presence or absence of non-reference levels is indicated by 1 and 0, respectively. As a result β^{ASC}, the parameter related to the alternative specific constant in the status quo alternative, captures the value of the current metering device and the effects of attributes and socio-demographic covariates not included in the model[20]. A negative value would indicate that respondents prefer to move away from the status quo, a positive value would indicate conservative preferences from the part of the respondent.

The CL model serves as reference for the RPL model discussed in section 5.2. Three versions of the CL model were estimated. The first model is based on the full sample of 228 households, the second model excludes respondents showing lexicographic choice behaviour and the third model excludes both lexicographic and non-trading responses.

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[18] The first reason was the overrepresentation in our sample of young, highly educated respondents in the higher income classes. A third argument to consider the WTP values we report as upper bounds for the real WTP value is that, in general, hypothetical bias is present in stated choice valuation studies (Murphy et al. (2005), Loomis (2011)). Hypothetical bias arises in stated preference valuation studies when respondents report a WTP that exceeds what they actually pay using their own money in laboratory or field experiments.

[19] Using effects coding allows to easily reconstruct the preference weights of the reference levels (β_0) as $\beta_0 = -\left(\beta_1 + ... + \beta_{L_k - 1}\right)$.

[20] We include only one alternative-specific constant. Alternatively, two alternative-specific constants could have been added, one for each non-status quo alternative. However, we imposed from the start the constraint that $\beta_1^{ASC} = \beta_2^{ASC}$, which is equivalent to only including β^{ASC}.

The first thing to note is that all statistically significantly estimated coefficients have the expected sign. Statistically significant estimates in model 1 remain significant in the models 2 and 3. In these latter models, two additional statistically significant effects are found for *Comfort level 1* and *Visibility level 1*. Furthermore, the null-hypothesis of having a zero alternative-specific constant is rejected in model 3.

We also reject the hypothesis that the estimated preference weights in model 1 are the same as those in the models 2 and 3, respectively[21]. The hypothesis that the estimates in model 2 are equal to those in model 3 cannot be rejected. We therefore decided to continue with model 3 to calculate WTP values. The model performance in terms of the pseudo-R^2 is lowest in model 2 and is comparable in model 1 and model 3.

INSERT TABLE 4 ABOUT HERE

The impact on utility of the percentage of '*cost savings*' is assumed to be linear. A quadratic specification was also tested, but resulted in a non-significant parameter (at the 5% level) for the quadratic term and did not significantly increase the explanatory power of the models. With the linear specification we find a statistically significant positive impact of the *Cost Savings* attribute on the respondent's utility. Only some qualitative attributes of the smart metering devices are found to have a significant effect on household utility. As mentioned before, we distinguish four qualitative characteristics: impact on comfort and privacy, visibility, and functionality of the device. Starting with the impact on *comfort* and focusing on CL model 3 we find that a 'shifting of services over time', with no or minor impact on comfort has a statistically significant positive impact on utility, an effect that was not found in model 1. However, interventions that would result in a decreased level of comfort (e.g. turning down the thermostat) are evaluated statistically significantly negative in the three CL models.

It was already discussed in section 4 that, in practice, the level of cost savings and the impact on comfort are correlated. In the experimental design used for this study, this correlation was not taken into account. One should therefore be cautious in interpreting and using the results, especially for the higher levels of the cost savings attribute[22]. Intuitively, if the experimental design used for this study would also have permitted to estimate the interaction effect between the comfort and cost savings attributes, then we expect to have found a negative preference weight attached to it, indicating that the value of increased cost savings is lower at higher levels of impact on comfort. Stated differently, we would expect consumers to be less sensitive to increased cost savings when the impact on comfort is higher.

Households have a preference for smart metering devices that do more than simply providing information about consumption (i.e. *monitoring*), although a very dynamic management of household appliances is not preferred. This outcome is found in all CL models.

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[21] Likelihood-ratio value for the models 1 and 2: $\chi^2 = 293.06; p = 0.000$; Likelihood-ratio value for the models 1 and 3: $\chi^2 = 38.82; p = 0.000$, both with 11 degrees of freedom.

[22] According to Louvière et al. (2003) (p. 88), ignoring an important interaction effect and using a strictly additive model (as we have done in this paper) will typically result in under- or overpredictions at the extremes of the utility space. However, around the center of the range of attribute levels, the model will predict relatively well.

Households clearly are concerned about the *privacy* impact of the smart metering equipment. A transfer of information towards the distribution company is disliked, especially when this would be combined with allowing the distribution company to take autonomous measures.

The last qualitative characteristic of the smart meter is *visibility*. In the models 2 and 3, households dislike devices that are visible, an effect that is not found in model 1.

Finally, the investment cost of the smart metering device has a significant and negative impact on household utility, indicating, as can be expected, that higher investment outlays for the metering device are disliked.

As always, the impact of each of these attributes has to be evaluated relative to the reference situation, which is a 'standard' metering device, implying the comfort, functionality, visibility and privacy conditions at the time the survey was filled out, with no cost savings relative to the current electricity bill and a zero additional investment requirement for the metering device. The value of the current situation is captured by the alternative-specific constant parameter and is negative in model 3, indicating that respondents have a preference towards smart metering devices.

5.1.1. Marginal WTP values based on the conditional logit model

As explained in section 2.2, the estimation results can be used to calculate marginal WTP values. These WTP values express the value of a change away from the current situation. We thus take the *current (status quo) situation* as the reference case for the WTP calculation, allowing to calculate WTP values as shown in equation (11)[23]. All three CL models generate very similar WTP results (except for the ASC). Therefore, Table 5 only shows the results for WTP values derived from model 3.

Respondents are willing to pay approximately €200 to move away from the standard metering equipment (all attribute levels are equal to zero) to a smart metering device. The null-hypothesis that this WTP equals zero is rejected (95% significance). Respondents also value cost savings: a one percentage point of savings on the annual electricity bill is valued €14. Keeping in mind the reservations made with respect to the experimental design, this estimate will likely hold best for lower levels of the cost savings attribute. Respondents are willing to pay €109 for a device that has no impact on comfort, while the willingness to pay for devices that only allow load shifting is just statistically significant at the 10% level. A smart meter that would reduce comfort levels by reacting on price signals (e.g. by turning the thermostat lower) is valued negatively, i.e. households are willing to pay €153 to avoid having a smart meter with this particular characteristic installed.

INSERT TABLE 5 ABOUT HERE

Smart meter functionality does not seem to influence its value very much. The results suggest that devices that can be programmed to autonomously shut down electrical appliances (for example a TV, when it is in 'stand by' modus for too long) are valued positively. On the other hand, respondents are neutral regarding smart metering devices

[23] Calculating WTP values relative to the *reference level of the attribute* (see Table 1), would require another expression.

that can respond dynamically to changing price signals. Devices with limited functionality, i.e. only monitoring and displaying electricity consumption levels of electric appliances, tend to be valued negatively.

Privacy characteristics have a large impact on the value of smart metering devices. Respondents are willing to pay about €160 for a device that has no privacy impact at all. Devices that would allow the distribution company to autonomously steer consumption are valued extremely negative. Respondents are willing to pay €155 to avoid such a device.

Finally, the visibility of the devices also seems to be of concern to the respondents. Devices installed *on* the wall are valued negatively. One is willing to pay €71 to avoid visibility of the devices.

5.2. The mixed logit model

In the mixed logit model, it is assumed that households have heterogeneous preferences regarding all characteristics of the smart metering technology. An exception is made for the bill attribute in order not to complicate the estimation of the willingness to pay values (Hensher and Greene (2003)). All random parameters are assumed to follow a normal distribution, except for the cost savings attribute which is assumed to follow a lognormal distribution. This latter distribution makes sense when a random parameter is expected to be either in the positive or the negative domain.

Similar to the approach followed in the previous section, we focus on estimating main effects. In addition, we also consider age, income and prior knowledge of the smart metering technology as explanatory variables. As noted before, our sample is biased towards younger and higher income respondents. We control for this by including age and income as explanatory variables and conjecture that age and income might impact preferences regarding smart metering devices via the cost savings attribute in the choice experiment[24]. The level of prior knowledge (see section 4) is interacted with the alternative specific constant. Here, we conjecture that if being more or less informed about the smart metering devices has an impact on preferences, then this will show up via more or less conservative choices. Equation (5) describes the basic structure of the mixed logit model. The random effects are assumed uncorrelated over the attributes.

The RPL estimates in Table 6 are based on the sample of 187 respondents, i.e. excluding both lexicographic and non-trading responses. The first thing to note is that the null hypothesis of a zero status-quo effect cannot be rejected. However, a significantly negative effect is found for respondents having a high knowledge level, indicating that these respondents are significantly more inclined to adopt a smart metering technology. In terms of significance and sign of the attribute parameters, the RPL and CL (model 3) estimates are very similar. The hypothesis of zero preference parameters for the income and age interaction variables cannot be rejected except for the low income group and the medium age group.

INSERT TABLE 6 ABOUT HERE

[24] We also interacted the age classes with the qualitative attributes of the devices, but, except for the interaction of age with privacy (negative sign) these effects were all non-significant.
Numerous models including other socio-demographic covariates as interaction variables were also estimated, with limited success. In this paper, we therefore only report outcomes for a model including age and income as interacted covariates.

Note that in the CL model the attribute parameters reflect preference information assuming homogenous preferences over households whereas in the RPL model these values provide an estimate of the mean of the distribution of preferences over households. Where a normal distribution of the preference parameter was assumed, the RPL estimates imply that a fraction of the respondents has preferences of opposite sign as the estimated sign of the preference mean. Thus, the estimate of the mean preference should be evaluated together with the estimate of the standard deviation of the preference distribution. These latter estimates are listed below the estimates of the mean.

Cost saving

The cost savings parameter follows a lognormal distribution. The estimated parameters shown in Table 6 are the mean and standard deviation of the natural logarithm of the cost savings coefficient. The mean and the standard deviation of the cost savings coefficient itself are 0.0695 and 0.1113, respectively. Both are significant at the 1% level. Also note that preferences for cost savings are lower for respondents in the low income class and respondents of medium age[25].

Comfort

Households have homogeneous preferences w.r.t. a rescheduling of services over time. The parameter estimate of the mean is positive and significant at the 5% level. This is not the case when the comfort level would reduce due to a reduction of the quality of the services provided: respondents strongly dislike this feature. Moreover, the hypothesis of homogeneous preferences cannot be rejected. These results are in line with the findings obtained in the conditional logit model.

Functionality

Smart metering devices that monitor electricity consumption and can be programmed to autonomously shut down unused electrical appliances (for example appliances in ‘stand by’ modus) are valued positively. Preferences for devices that can autonomously intervene based on price information are on average not valued. Again, these results are in line with the outcome of the conditional logit model. For both levels of functionality we cannot reject the hypothesis of preference homogeneity.

Privacy

A large share of households dislikes reduced privacy levels. Regarding the intermediate privacy impact (information regarding the electricity load profile is transmitted to the distribution company), average preferences seem to be close to neutral, but the estimate of the standard deviation suggests that preferences are heterogeneous. Overall, this implies that close to 50% of households do not oppose to the idea of having load information transferred to the distribution company.

The conclusion is different when the distribution company would be able to autonomously steer electricity demand. Here, the average household has a clear

[25] The income variable is categorical and distinguishes three classes: ‘low income’ (net monthly household income less than or equal to €2500), ‘medium income’ (net monthly incomes between €2501 and €4000) and ‘high income’ (net monthly incomes above €4000). The ‘income not available’ category is taken as the reference category.

disutility, although preferences are heterogeneous. About 80% of households dislike this type of smart metering.

Visibility

Respondents seem to have heterogeneous preferences with regard to the visibility aspects of the smart metering device. About 80% of respondents dislike having the equipment devices installed *on* the wall (i.e. on the electricity socket, therefore visible). Preferences are more neutral and homogeneous regarding the option of having metering devices installed in the electrical appliances.

Investment cost

Finally, the investment cost attribute is – as expected, and in line with the results of the CL model – negative and statistically significant at the 1% level.

5.2.1. Marginal willingness to pay based on the mixed logit model

Following a similar approach as with the CL model, we generate WTP estimates for the RPL model. Using equation (11) we find the results summarized in Table 7. Note that these WTP values are estimates for the average household within that group. Upper and lower bounds should be interpreted as a 95% confidence interval for this estimate and should not be interpreted as the range of WTP values that emerges as a consequence of the heterogeneity of preferences. The latter interval would be wider, because of the estimated variation in preferences.

The negative WTP linked to the alternative-specific constant reflects the respondent's willingness to move away from the status quo (*ASC=1* for the standard meter). Respondents with better prior knowledge of smart applications show an even higher willingness to move towards a smart metering device. Clearly, having prior knowledge about smart metering has a positive impact in the willingness to adopt the technology.

INSERT TABLE 7 ABOUT HERE

The mean WTP for one percentage point of savings on the annual electricity bill is statistically significant at the 1% level and equals €30 for a respondent younger than 36 with unknown monthly household income. Taking into account age and income, the WTP ranges between €18 and €36. All values are statistically significant but, in our sample, we do not find statistical evidence to support the hypothesis that the WTP for an extra percentage point of cost savings depends on age or income. Keeping in mind the untreated correlation between the cost savings and the impact on comfort attributes, these estimates will thus likely hold best for lower levels of the cost savings attribute.

These results allow deriving the household's implicit rate of time preference for money. For example, according to the Belgian Household Budget Survey of 2012 (see footnote 14), a respondent with average household income (€3900 per month) has an annual electricity bill of approximately €850. Assuming that this respondent is aged 36 to 50, a one percentage point of cost savings would imply an annual reduction in the electricity bill of €8.5. With a WTP of €29 (a one-time payment) for one percent of cost savings on the annual electricity bill and assuming an infinite time horizon, this implies a discount rate of $8.5/29 \cong 29.3\%$. Note that with a WTP of €29, assuming shorter time horizons would hardly make any difference in terms of implied discount rate. For example with a 10 year time horizon, the implied discount rate would equal 26,5%.

According to our results, a respondent aged between 36 and 50 with a household income in the low income class is willing to pay €18 for a 1% cost savings on the annual electricity bill. Based on the Belgian Household Budget Survey, we estimate the annual electricity bill at around €700 for this income class. Taking this value as an approximation, the implicit discount rate for this respondent would be $7/18 \cong 38.9\%$ (37.3%, with a 10-year time horizon). A respondent older than 50 in the high income class would spend approximately €1000 on electricity. Assuming a willingness to pay of €32 for a 1% cost savings, the implicit discount rate would be $10/32 \cong 31.3\%$ (28.8%, with a 10-year lifetime horizon).

Looking at the qualitative characteristics of the smart metering device, we see that the conditional logit and random parameter models generate quite similar results, at least in terms of the order of magnitude or the WTP values. We find a significantly positive mean WTP for a device that allows monitoring and can autonomously shut down appliances (*functionality*). Furthermore, the average respondent has a significantly negative willingness to pay to avoid a metering device that allows for reduced energy service levels (*comfort*), for external intervention by the distribution company (*privacy*) or is installed on the wall (*visibility*).

5.2.2. Willingness to pay for a smart metering device

From a purely financial perspective, the implied internal rates of return of the devices offered in the choice experiment are extremely high, ranging from 23% for the most expensive device (costing €350), resulting in an annual saving on the electricity bill of €80 (10% on €800, the average electricity bill in Flanders) over an infinity time horizon, up to 480% for the cheapest device (costing €100) and resulting in an annual cost saving on the bill of 60%. This means that, from a purely financial perspective and given an implicit discount rate of approximately 29%, most devices *offered in the experiment* are worth buying. Once again, note that these devices all imply levels of cost savings of 10% or more. For the more realistic scenarios with cost saving around 10% or less (and from a purely financial perspective) most smart metering devices will not be worth buying.

However, the impact on privacy and comfort, and the visibility and functionality features of the devices will also affect the value for the consumer. In Table 8, we therefore calculate the value for the customer of moving from a standard meter to a smart meter with the features described in the table. The customer is assumed to be a reference customer in the sense that he values a 1% of cost savings on the annual electricity bill at 30€. For the reasons discussed before, this should be interpreted as an upper bound for this WTP. The first meter is a very basic one that monitors electricity consumption, is installed on the wall and results in an annual reduction of the electricity bill of 3%. Respondents without prior knowledge of smart applications are willing to pay just over €300 for this device if, in addition, it has no impact on comfort and privacy. If the device would have a small impact on comfort levels, for example because using the washing machine is shifted to the evening, and load information is communicated to a third party, then the value of the smart meter reduces to €38. If this third party could also actively intervene, then the value of the device becomes negative, i.e. the respondent is willing to pay to avoid the device.

INSERT TABLE 8 ABOUT HERE.

All other devices in the table, are identical to this basic device except for one or two features, relating to the percentage of cost saving, the functionality or the visibility of the device. From the table, we learn that the more advanced a smart meter becomes in terms of automated response or third party intervention (and thus privacy impact) the less it is valued by the respondents. The amount of cost savings that can be realised then becomes crucial to assess its market potential. However, evidence from pilot studies suggests that these savings are likely to be insufficient to compensate for this. According to Giordano et al. (2013), 3% would be a conservative estimate of cost savings, but results for 7% of cost savings are also presented. Both levels are insufficient to compensate for a large privacy impact. Another element with positive impact on the valuation of a smart meter is the level of prior knowledge, as can be seen by comparing the first and the third block in Table 8. However, this effect in itself seems insufficient to compensate the negative contributions to the value of a smart meter that are due to privacy and comfort effects. Well-informed consumers and an invisible installation (block 6) are required to at least obtain a positive valuation of a smart metering device with large impact in comfort and privacy, let alone to have a value that outweighs the investment cost of the device.

6. Conclusions

This paper tackles the question of whether and to what extent households are willing to pay for smart metering devices with varying characteristics. The data were collected in Flanders via a choice experiment in which smart meters are described by their investment cost, their cost savings potential, and their effect on comfort, functionality, privacy and visibility. Respondents showing lexicographic choice or non-trading behaviour were removed from the dataset. The data were used to estimate a main effects conditional logit model and a main effects random parameter logit model, the latter including interaction effects to control for age, income and prior knowledge of smart metering technology.

Our sample is not representative for the Flemish population, as we have an overrepresentation of young and highly educated respondents in the higher income ranges. We can thus not simply generalize our findings to the Flemish population, let alone to other regions or countries. Nevertheless, given the characteristics of our sample, we can probably interpret the WTP values calculated in this paper as an upper bound for the real WTP values. We also find support for the hypothesis that preferences for some of these attributes are heterogeneous (for the ‘cost savings potential’, ‘privacy impact’ and ‘visibility’). Taking into account preference heterogeneity and the presence of non-trading behaviour, we do not find evidence for a status quo effect for respondents with little prior knowledge of smart technologies. Respondents with good prior knowledge of smart technologies have a clear preference to move away from the standard metering device installed in their homes.

From a policy perspective, the results are interesting as they suggest that a sizeable proportion of households might be reluctant to voluntarily switch to a smart meter. Unless a smart meter is equipped with features and characteristics that support consumer engagement, it might not create the potential benefits it is claimed to create. From a household’s perspective, the private value of the device, taking into account its main characteristics, is too low to justify the investment. Even with a mandatory roll-out it is not clear whether households will be willing to take full advantage of the device. Realising the full social and private benefits linked to the devices would require households to switch to an electricity contract that involves dynamic pricing, with automated and/or third party control of electric appliances in their homes (Faruqui et al. (2010), Giordano et al. (2013)). These are exactly the features that receive lowest (or even negative) value in our study. The results thus suggest that it would not be a good idea, from a policy perspective, to organize a mandatory roll-out of the technology, at least not without first tackling the issues that are negatively valued by the respondents.

One element of the solution to this problem could be the provision of information to the customer. Indeed, our results also suggest that providing sufficient information to the public about the benefits and costs of ‘smart technologies’ could help to increase the market potential of the devices. In that sense, it would be interesting to have a closer look at the impact on consumer preferences of the large field experiment with 50.000 households that was initiated in 2012. For the participants to this field experiment, both knowledge and preferences might have changed.

As mentioned before, our sample is not representative. Nevertheless, our results suggest (an thereby are in line with the conclusion by Stromback et al. (2011)) that the design of a smart metering device can have a large impact on how much of its demand response potential can be exploited. The design of the devices thus needs careful attention before deciding on its roll-out, but further analysis on larger and more representative samples is needed for this.

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Appendix A : The choice experiment question

The section containing the choice experiment questions starts with the following introduction, followed by a description of all attributes and the corresponding levels. The nine choice questions are then presented one by one. They all comprise a table similar to the table below and a brief attribute description.

Introductory screen

In the following nine questions you must select one out of three available options. Option 1 and Option 2 each represent a smart home application that reduces energy consumption at your home. An application has six major properties. Please select the application that you prefer. If you prefer neither option, then choose the current situation (option 3).

1. Investment cost (to be paid once): €100, €200 or €300.
2. Functionality of the application:
   a. Monitoring: provides information on energy use for all electrical applications, at any moment of the day.
   b. Monitoring and (dis)connection: monitoring + disconnecting electrical appliances (for example applications in stand-by modus).
   c. Dynamic management of appliances: energy price information can be used to start up or stop electrical appliances.
3. Visibility:
   a. In the wall: the device is integrated in the power outlet.
   b. On the wall: the device is installed on the wall.
   c. In electrical appliances: the device is integrated in electrical appliances.
4. Impact on privacy:
   a. None: no impact on privacy
   b. Information is communicated to network operator;
   c. Information is communicated to the network operator and third party intervention is possible (for example in case of an imminent power outage or grid overload).
5. Impact on comfort:
   a. None: no impact on the perceived comfort level.
   b. Shifting of load in time: for example, the application can autonomously decide to run the washing machine during the night.
   c. Reduced comfort level: for example, the application can autonomously decide to change the in-house temperature.
6. Cost saving: annual reduction of the electricity bill obtained via the application
   a. 10%, 20%, 30%, 40%, 50% or 60%

In each of the presented choice sets, select the option you prefer.

Example of one choice experiment question

Which option do you prefer?

	Option 1	Option 2	Option 3
Investment cost	€100	€200	Current situation
Functionality	Monitoring	Monitoring and disconnection	
Visibility of the installation	In the wall	On the wall	
Privacy	No impact	Information is transmitted	
Loss of comfort	None	Shift applications in time	
Cost savings	10%	20%	

Option 1	Option 2	Option 3
☐	☐	☐

<u>Brief description of the attributes</u>

- <u>Investment cost</u>: on-time payment to get the smart home application in your house.
- <u>Functionality</u>: the different functions that the smart home application has.
- <u>Visibility</u>: how is the application integrated in your house?
- <u>Privacy</u>: the extent to which third parties have access to information about your energy consumption.
- <u>Comfort</u>: the extent to which the application affects your comfort level.
- <u>Cost saving</u>: annual reduction of the electricity bill obtained via the application.

Appendix B : Description of the choice sets and the choice frequencies.

Survey	Choice card	Profile	invCost	Funct	Visib	Privacy	Comfort	Cost Savings	Frequency
1	1	1	100	0	0	0	0	0.1	43,1%
1	1	2	200	1	1	1	1	0.2	48,3%
1	1	3	Status Quo						8,6%
1	2	1	200	2	2	0	1	0.2	47,8%
1	2	2	350	0	0	1	2	0.3	40,8%
1	2	3	Status Quo						11,3%
1	3	1	350	1	2	1	0	0.3	25,9%
1	3	2	100	2	0	2	1	0.4	53,6%
1	3	3	Status Quo						20,5%
1	4	1	200	1	0	2	2	0.4	22,0%
1	4	2	350	2	1	0	0	0.5	66,1%
1	4	3	Status Quo						11,9%
1	5	1	350	0	0	2	1	0.5	15,9%
1	5	2	100	1	2	0	2	0.6	71,0%
1	5	3	Status Quo						13,1%
1	6	1	100	2	1	1	2	0.6	64,1%
1	6	2	200	0	2	2	0	0.1	12,3%
1	6	3	Status Quo						23,6%
1	7	1	200	1	1	1	1	0.1	28,3%
1	7	2	350	2	2	2	2	0.2	33,7%
1	7	3	Status Quo						33,0%
1	8	1	350	0	0	1	2	0.2	12,5%
1	8	2	100	1	1	2	0	0.3	62,5%
1	8	3	Status Quo						25,0%
1	9	1	100	2	0	2	1	0.3	28,8%
1	9	2	200	0	1	0	2	0.4	59,6%
1	9	3	Status Quo						11,6%
2	1	1	350	2	1	0	0	0.4	31,3%
2	1	2	100	0	2	1	1	0.5	58,9%
2	1	3	Status Quo						9,8%
2	2	1	100	1	2	0	2	0.5	29,7%
2	2	2	200	2	0	1	0	0.6	56,8%
2	2	3	Status Quo						13,5%
2	3	1	200	0	2	2	0	0.6	61,3%
2	3	2	350	1	0	0	1	0.1	21,6%
2	3	3	Status Quo						17,1%
2	4	1	350	2	2	2	2	0.1	6,5%
2	4	2	100	0	0	0	0	0.2	81,4%
2	4	3	Status Quo						12,1%
2	5	1	100	1	1	2	0	0.2	18,7%
2	5	2	200	2	2	0	1	0.3	64,5%
2	5	3	Status Quo						16,8%
2	6	1	200	0	1	0	2	0.3	17,8%
2	6	2	350	1	2	1	0	0.4	63,5%
2	6	3	Status Quo						18,7%
2	7	1	100	0	2	1	1	0.4	29,9%
2	7	2	200	1	0	2	2	0.5	46,7%
2	7	3	Status Quo						23,4%
2	8	1	200	2	0	1	0	0.5	41,1%
2	8	2	350	0	1	2	1	0.6	38,3%
2	8	3	Status Quo						20,6%
2	9	1	350	1	0	0	1	0.6	69,8%
2	9	2	100	2	1	1	2	0.1	11,3%
2	9	3	Status Quo						18,9%

Table A.1: Basic frequencies responses per choice card.

Attribute	Description	Levels	Nr of levels
Investment cost (€)	One-time payment to adopt the smart meter. The smart meter is sold as a package that allows to 'control' up to six electrical appliances.	€100, €200, €350.	3
Cost Savings (% point annual bill)	These devices result in reduced electricity demand. The size of this effect is however unknown.	10%, 20%, 30%, 40%, 50%, 60%.	6
Comfort impact	Depending on the type of actions taken by the device, the impact on the comfort level can range from negligible to substantial.	- No impact (Reference level); - Load shifting from peak to off-peak with little impact on comfort; - Reduced comfort level.	3
Functionality	The minimum service is simply monitoring of load. In addition, the device might be programmed by its owner to shut down unused devices and/or to autonomously act upon information regarding load or price.	- Only monitoring. (Reference level); - Monitoring and (dis)connecting appliances; - Dynamic management of appliances.	3
Privacy impact	The device might or might not transfer load data to third parties. Moreover, these third parties might be allowed to actively intervene by shifting or shedding load.	- No effect (Reference level); - Load profile communicated to network operator; - Load profile communicated to network operator and intervention is possible.	3
Visibility	The visual impact of the device.	- In the wall (not visible) (Reference level); - On the wall (in socket, visible); - In appliances (not visible).	3

Table 1: Attributes and levels used in the choice experiment.

Variable Name		Sample	Flemish Population
Sex	Male	76,2%	49,4%
	Female	23,8%	50,6%
Age distribution	<35:	31,6%	23,5%
	36 to 49:	36,4%	27,6%
	≥ 50:	32,1%	48,9%
Education	Secondary school:	17,1%	67%
	Higher education:	82,9%	33%
Net monthly household income	≤ €2500:	17,6%	
	€2501 - €4000:	33,2%	
	≥ €4001:	31,1%	
	Unknown:	18,1%	
Annual electricity bill	Average:	€1087	€836
	std. deviation.	€1477	
Annual electricity consumption	Average:	-	4000 kWh
Average flat rate (€/kWh)		-[a]	€0.209[b]
Average price when TOU pricing scheme applies (€/kWh)		-[a]	€0.160 – €0.210[c]

[a]: Our dataset does not allow distinguishing between households according to the type of tariff they subscribed to.

[b]: Calculated (weighted) price in the last quarter of 2010 for a standard household consumer (4 people), consuming 3500kWh per year, taking into account the market shares of the incumbent and the main alternative supplier (CREG (2011)).

[c]: Calculated price range for main suppliers in the first quarter of 2011 for a standard household consumer (4 people), consuming 3500kWh per year (1900kWh night/weekend;1600kWh daytime) (CREG (2012)).

Table 2: Some descriptive statistics.

	Percentage Interested in…?				
	measuring standby consumption	*measuring consumption per device*	*the timing of consumption*	*automated response to real time price*	*the total package*
Not Interested	8,33	9,21	10,53	7,89	7,02
Moderately	12,72	14,91	21,49	14,47	10,96
Interested	25,00	28,07	27,19	30,26	27,63
Highly Interested	33,33	32,89	29,39	29,39	31,14
Extremely Interested	20,61	14,91	11,40	17,98	23,25

Table 3: Interest in different capabilities of a smart meter (228 respondents).

Attribute	Model 1 All obs	St. err.	Model 2 Non-lex. Beh.	St. err.	Model 3 Non-lex. Beh. & trading	St. err.
ASC3	-0,1000	0,1502	-0,1105	0,1641	-0,3977**	0,1772
CostSavings	0,0309***	0,0029	0,0242***	0,0027	0,0272***	0,0030
Comfort						
Load Shifting, little impact	0,0542	0,0372	0,0819*	0,0421	0,0857*	0,0443
Reduced comfort	-0,2412***	0,0469	-0,2832***	0,0525	-0,2986***	0,0533
Functionality						
Monitoring and disconnection	0,0721**	0,0339	0,0851**	0,0394	0,0928**	0,0423
Dynamic Management	-0,0061	0,0375	0,0017	0,0434	-0,0097	0,0459
Privacy						
Load profile communicated	-0,0371	0,0435	-0,0080	0,0490	-0,0133	0,0512
Load profile communicated and intervention possible	-0,2799***	0,0473	-0,2829***	0,0524	-0,3006***	0,0537
Visibility						
On the wall	-0,0684	0,0454	-0,1120**	0,0518	-0,1374**	0,0533
In appliance	0,0032	0,0370	-0,0189	0,0422	-0,0129	0,0431
InvCost	-0,0016***	0,0003	-0,0020***	0,0004	-0,0019***	0,0004
Nr. Choice sets	5,865		4,629		4,305	
Pseudo R^2	0,133		0,0911		0,144	
Nr. of clusters	228		199		187	
Loglikelihood	-1862		-1541		-1350	
k	11		11		11	

Table 4: Estimation of main effects for the Smart Meter Choice Experiment after deleting observations showing apparent lexicographic behaviour and/or non-trading behaviour

	Low. Bound[a]	*WTP*	*Up. Bound*[a]
Alt. Spec. Constant	-€365	-€204**	-€44
Cost savings	€7	€14***	€21
Comfort			
No impact	€49	€109***	€169
Load Shifting, little impact	-€6	44*	€94
Reduced comfort	-€234	-€153***	-€73
Functionality			
Only monitoring	-€93	-€43*	€7
Monitoring and disconnection	€1	48€*	€94
Dynamic Management	-€51	-€5	€41
Privacy			
No effect	€73	€161***	€249
Load profile is communicated	-€59	-€7	€45
Profile communicated, intervention possible	-€234	-€155***	-€74
Visibility			
In the wall	€19	€77***	€136
On the wall	-€131	-€71**	-€11
In appliances	-€50	-€7	€37

[a] 95% Confidence interval, estimated with the Delta method.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: WTP estimates derived from the CL model 3.

		Coefficient		St. Err	%>0
Alt. Spec. Constant		0,1604		0,2075	
ASC_No Knowledge		-0,2593		0,1826	
ASC_Well Informed		-0,7233	***	0,2347	
Investment Outlay		-0,0023	***	0,0004	
Cost savings	Mean	-3,3023	***	0,1435	
	SD	1,1276	***	0,1231	
Age 36 -50		-0,0097	**	0,0044	
Age older than 50		0,0061		0,0045	
Low income (≤ €2500)		-0,0176	***	0,0061	
Medium income (€2500 – €4000)		0,0074		0,005	
High income (≥ €4000)		-0,0004		0,0053	
Comfort					
Load Shifting, little impact	*Mean*	0,1176	**	0,0583	100.0%
	SD	0,0119		0,3375	
Reduced comfort	*Mean*	-0,4040	***	0,0709	1.1%
	SD	0,1772		0,172	
Functionality					
Monitoring	*Mean*	0,1455	**	0,0601	98.9%
and disconnection	*SD*	0,0631		0,2005	
Dynamic Management	*Mean*	-0,0387		0,0617	29.2%
	SD	0,0708		0,2684	
Privacy					
Load profile	*Mean*	-0,0252		0,0655	47.4%
is communicated	*SD*	0,3915	***	0,0970	
Load profile communicated	*Mean*	-0,4005	***	0,0744	18.0%
and intervention possible	*SD*	0,4373	***	0,1026	
Visibility					
On the wall	*Mean*	-0,2065	***	0,0691	21.8%
	SD	0,2647	**	0,1154	
In appliances	*Mean*	-0,0042		0,0596	46.0%
	SD	-0,0417		0,2162	
Statistics					
N		4305			
Log Likelihood		-1.247			

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: Mixed Logit Estimation results.

Attribute		***WTP (95% Conf. Int.)[a]***	
Alt. Spec. Const			
No knowledge		-€43*** (-€176 / -€91)	
Knowledge		-€243*** (-€491 / -€4)	
	Low income[b]	***Medium income[b]***	***High income[b]***
Cost savings			
Younger than 36	€24*** (€10 / €31)	€35*** (€19 / €51)	€31*** (€16 / €47)
Age between 36 and 50	€18*** (€6 / €31)	€29*** (€15 / €43)	€26*** (€13 / €39)
Older than 50	€25*** (€11 / €39)	€36*** (€19 / €52)	€32*** (€17 / €48)
Comfort			
No impact		€124*** (€58 / €189)	
Load Shifting, little impact		€51 (-€3 / €105)	
Reduced comfort		-€175*** (-€260 / -€90)	
Functionality			
Only monitoring		-€46** (-€99 / -€6)	
Monitoring and disconnection		€63** (€8 / €118)	
Dynamic Management		-€17 (-€70 / €36)	
Privacy			
No effect		€184*** (€91 / €277)	
Load profile is communicated		-€11 (-€67 / €45)	
Profile communicated, intervention possible		-€173*** (-€256 / -€90)	
Visibility			
In the wall		€91*** (€28 / €154)	
On the wall		-€89** (-€158 / -€20)	
In appliances		€-2 (-€52 / €48)	

[a] 95% Confidence interval, estimated with the Delta method.
[b] *Low income: ≤ €2500; Medium income: €2500 – €4000; High income: ≥ €4000*
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7: WTP values and 95% conf. interval based on the RPL model 3.

			Privacy impact	
1.	*Reference Case (No prior knowledge; Percentage cost savings = 3%; Only monitoring; Installed on the wall)*			
		No effect	**comm. to DisCo**	**DisCo controls Apps**
Impact on comfort	**¤ No effect**	€306	€111	-€51
	Little impact	€233	€38	-€124
	Reduced Comfort	€7	-€188	-€350
2.	*Reference case with percentage of cost saving = 7%*			
		No effect	**comm. to DisCo**	**DisCo controls Apps**
Impact on comfort	**No effect**	€426	€231	€69
	Little impact	€353	€158	-€4
	Reduced Comfort	€127	€-68	-€230
3.	*Reference case with good prior knowledge*			
		No effect	**comm. to DisCo**	**DisCo controls Apps**
Impact on comfort	**No effect**	€506	€311	€149
	Little impact	€433	€238	€76
	Reduced Comfort	€207	€12	-€150
4.	*Reference case with percentage of cost saving = 7% and good prior knowledge*			
		No effect	**comm. to DisCo**	**DisCo controls Apps**
Impact on comfort	**No effect**	€626	€431	€269
	Little impact	€553	€358	€196
	Reduced Comfort	€327	€132	-€30
5.	*Reference case with monitoring and disconnection, and good prior knowledge*			
		No effect	**comm. to DisCo**	**DisCo controls Apps**
Impact on comfort	**No effect**	€615	€420	€258
	Little impact	€542	€347	€185
	Reduced Comfort	€316	€121	-€41
6.	*Reference case with device installed in the wall and good prior knowledge*			
		No effect	**comm. to DisCo**	**DisCo controls Apps**
Impact on comfort	**No effect**	€686	€491	€329
	Little impact	€613	€418	€256
	Reduced Comfort	€387	€192	€30

Table 8: Value of smart meters.

Highlights

- Are consumers willing to make use of the capabilities offered by smart meters?
- Households have heterogeneous preferences for some attributes but not for others.
- Effort should be devoted to carefully designing the devices.
- A mandatory or voluntary roll out of smart meters risks to be unsuccessful.